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On the potential of traffic light information availability for reducing fuel consumption and $\mathrm{NO_x}$ emissions of a diesel light duty vehicle

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Abstract

The paper addresses the impact of traffic light information availability in terms of fuel consumption and emissions by means of comparing 3 different scenarios that a driver of a diesel light duty vehicle may face when trying to cover a particular route of 1km with two traffic lights in between. The first scenario is that the driver does not know in advance the state of the traffic lights. The second scenario assumes that the driver knows the state of the traffic lights but has not modelling nor computation capabilities to solve the associated Optimal Control problem. In the third scenario, the driver knows in advance the state of the traffic lights and also is able to solve the corresponding Optimal Control problem that leads to fuel consumption or $\mathrm{NO_x}$ emissions minimisation. In the present study the vehicle speed trajectories associated to the previously described 3 scenarios have been computed and then tested in a Euro 5 Diesel vehicle installed in a chassis dynamometer. The obtained results show that: Traffic light information is essential for fuel minimisation in urban conditions, promoting reductions of 7.5-12% and 13-32% for fuel consumption and $\mathrm{NO_x}$ emissions in the studied case. Also, differences in the engine operating conditions for high efficiency and low $\mathrm{NO_x}$ emissions may lead to extremely high fuel consumption when $\mathrm{NO_x}$ minimisation is foreseen or viceversa.

Keywords

Eco-driving; Velocity profile optimisation; Optimal Control; Real driving cycle; Fuel consumption optimisation; NOx emissions optimisation

Introduction

During last decades important research efforts have been focused on the development and integration of engine technologies aimed to improve fuel efficiency and emissions of light duty vehicles[1]. Those efforts have materialised in important reductions in emissions and fuel consumption according to regulation cycles, however, their impact on real driving is limited[2,3]. Amongst other reasons, the vehicle operating conditions play a major role in global efficiency and emissions, therefore, differences between real driving and regulation cycles give rise to the usual fact that the actual consumption exceeds that from the vehicle specifications.

The research community has been traditionally more focused on the engine design including realistic driving conditions[4] or even close loop emissions control[5] than on the optimisation of vehicle operating conditions due to the intrinsically complex nature of this optimisation problem. Note the lack of controllability of the system since the driver manipulability is, at least, arguable, and it is evident that there are other factors affecting driving that are completely out of control (reactions of other drivers, weather,...). Nevertheless, the improvement of computation capabilities, the introduction of Optimal Control in powertrain management and the increase of cost-effective sensors and information sources (GPS, V2V, V2I,...) have lead to an intensive research activity in the optimisation of the velocity profile, also known as eco-driving, with the aim of reducing the fuel consumption[6–8].

Previous studies try to address an extremely complex problem and need to apply different degrees of simplification. Amongst others:

- Quasi-static models for the engine coming from experimental measurements or algebraic functions are used. In this sense, engine dynamics are neglected.
- The objective function is the fuel consumption without considering other performances that can be of interest, for example emissions.

Despite some works have applied Optimal Control to vehicle powertrains without the so called quasi-static engine simplifications[9,10], very simplistic 0D models should be applied, and the obtained problem is still really complex to be solved. For this reason, the present paper considers the quasi-static engine approximation previously followed in other works[6–8]. On the contrary, taking into account that engine operating areas with minimum fuel consumption do not, in general, coincide with those of minimum emissions

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(particularly NO_x emissions), the present paper discusses, what is the impact on NO_x emissions of fuel optimal driving strategies and what is the potential of driving strategies aimed to minimise NO_x emissions instead of fuel consumption.

In particular, the paper addresses the impact of traffic light information availability in terms of fuel consumption and emissions by means of comparing 3 different scenarios when a driver faces a route with traffic lights. The first scenario is that the driver does not know in advance the state of the traffic lights, so he applies a sensible strategy, i.e. keeping constant velocity from the start to the end (if possible) to cover the distance in the required time. Of course, depending on the state of the traffic lights, the driver will need to correct his strategy due to stops. One may expect that if the driver needs to stop due to a traffic light, and spend some time stopped, then the increase in velocity needed to finish the route in the desired time may involve a noticeable penalty in terms of fuel consumption. The second scenario assumes that the driver knows the state of the traffic lights but has no modelling nor computation capabilities to solve the associated optimal control problem. In this case, a simple strategy is proposed and evaluated in the paper, which is based on keeping velocity as constant as possible without having to stop in a traffic light. In the third scenario, the driver knows in advance the state of the traffic lights and also has modelling and computation capabilities to solve the corresponding Optimal Control problem that leads to fuel consumption or NO_x emissions minimisation. The study is carried out considering a particular driving route of 1km with two traffic lights in between. The comparison of the performance of the previous strategies under different scenarios will lead to conclusions on the potential of the traffic light information to improve the fuel consumption and emissions of the vehicle.

The paper is organised as follows: The first part is dedicated to describe the problem to be addressed and the tools used, i.e. model, optimisation techniques and experimental set up. In the second part, the results obtained are presented and analysed to conclude with a summary of the paper contributions.

Problem description

The problem addressed in the present paper is to cover a particular route in less than a given time with minimum fuel consumption, or NO_x emissions, provided that several traffic lights are within the route. In particular, the route analysed is that of figure 1, where l represents the route distance, l_0 and L are the starting and ending points respectively, while l_{TLi} represents the position of traffic light i. Any of the traffic lights has its own period (T_{TLi}) and a time at red ($t_{red,TLi}$). For the sake of simplicity, it is assumed that the traffic light goes directly from green to red (no orange lighting is considered). The particular values of the previous variables employed in this study are shown in table 1

Proposed solutions

Amongst the variables affecting the solution to a given optimisation problem, one may find three that are specially relevant:

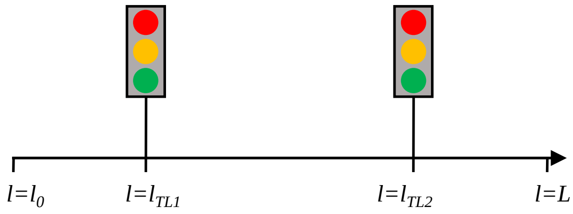

Figure 1. Scheme of the route analysed.

Table 1. Route description.

Variable	value
l_0	0 m
L	1000 m
l_{TL1}	250 m
l_{TL2}	750 m
T_{TL1}	90 s
T_{TL2}	90 s
$t_{red,TL1}$	30 s
$t_{red,TL2}$	30 s

- The optimisation objective. In the case at hand, two different objectives are to be considered. First, the minimisation of the fuel consumption. Then, the minimisation of the NO_x emissions since it is the most critical emission in Diesel powered vehicles and there is an increasing concern about Diesel vehicle NO_x emissions in urban areas. Note that a multi-objective optimisation can be carried out considering a cost function weighting both fuel and NO_x emissions like in works addressing the energy management of Diesel Hybrid Electric Vehicles[11,12].
- The information availability. In this case, two opposite situations are considered: the case where there is no information about the state of the traffic lights and the situation where the state of the traffic lights is a priori known.
- The computation burden. An online application of the strategy will require an estimator for fuel consumption and emissions (model) and a real time optimisation tool while generally, both have high computation. In this sense, two different situations are considered: the situation where there are no computation restrictions that allow the application of Optimal Control techniques, in the case at hand Dynamic Programming, and a sub-optimal solution with real time application. Note that if traffic disturbances are neglected, the vehicle speed trajectories can be precomputed and applied according to the traffic lights state.

Taking into account the previous aspects, 4 strategies are evaluated in the present paper:

(i) Driver without traffic light information ($woTLI$): In this situation, the driver does not have information on the current and future state of the traffic lights. Taking into account that his objective is to cover the distance L within a time frame $[0, T]$, a sensible strategy is to

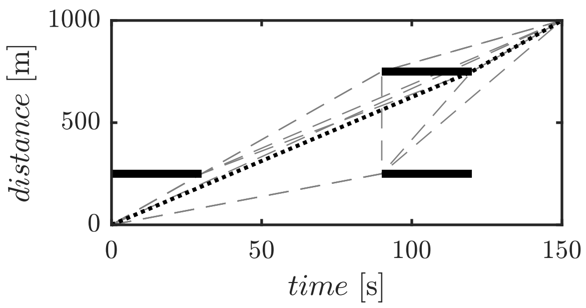

Figure 2. Scheme of the possible trajectories in the time-space plane that are considered in strategy $wTLI$ (in grey). The black thick lines represent traffic lights in red that can not be crossed, while the black dotted line shows the optimal trajectory in the sense of equation 2

try to set a target velocity (v_{sp}) such that:

$$v_{sp}(t) = \frac{L - l(t)}{T - t} \qquad (1)$$

Of course, depending on the state of the traffic lights, the driver may have to stop. According to equation 1, from this point the objective velocity $v_{sp}(t)$ will be increased to compensate for the stopped time.

(ii) Driver with traffic light information ($wLTI$): It is rather intuitive that keeping the velocity as constant as possible has a positive impact on engine efficiency, since the inertial term in the energy balance (eq. 7) is minimised. It is also intuitive that stopping the vehicle in a traffic light should be avoided to minimise fuel consumption and emissions since on one hand it involves a kinetic energy dissipation during breaking followed by an energy expenditure to accelerate the vehicle again, and on the other hand it will force a higher velocity after the traffic light to compensate for the time stopped. According to the above arguments, a solution close to the optimum in the case without traffic lights would be to maintain a constant average speed that would take the vehicle to the end of the trip at the desired time. For sure, the existence of traffic lights will often make this solution infeasible, but knowing when the state of the traffic lights changes can be used to consider a limited number of cases in which the vehicle speed is as constant as possible. In this sense, the proposed strategy consists of considering a set of segments with constant velocity, and then choose the combination with the lower velocity variations that does not incur in passing through a traffic light in red. The case at hand, with 2 traffic lights, leads to the 9 trajectories of constant velocity segments without crossing the traffic lights in red represented in figure 2.
From an implementation point of view, the three following aspects should be considered:

- This strategy is not optimal in terms of fuel consumption, nor NO_x emissions since the quantity to minimise is how the velocity is deviated from the constant velocity, provided some restrictions on the vehicle position at different times (i.e. the vehicle should pass through the position of every traffic light when its state is green). The optimisation problem can be stated as:

$$\begin{aligned} & min \left\{ \sum_{j=1}^{j=n} \left(v_{sp,j} - \frac{L}{T} \right)^2 \right\} \\ & s.t. \\ & TL_i \left(l = l_{TL_i} \right) = green \end{aligned} \qquad (2)$$

where n is the number of segments in the route ($n-1$ is the number of traffic lights), $v_{sp,j}$ is the vehicle speed set point (the decision variable) in the segment j, and $TL_i \left(l = l_{TL_i} \right)$ is the state of the traffic light i when the vehicle passes through its position l_{TL_i}. According to the previous idea, this strategy does not require a model for fuel nor NO_x emissions since does not consider those variables.
- Strategies $woTLI$ and $wTLI$ provide exactly the same result if covering the distance at constant speed does not involve crossing a traffic light in red.
- Note that the calculation of the possible trajectories can be done offline, so the computation cost on board is strongly reduced.
- Note that the number of constant speed segments (see figure 2) depends on the number of traffic lights since the timing when they change their state is used as a starting of ending point of the segment. Despite, in the case at hand, the number of cases to be tested is small, its number rapidly increases with the number of traffic lights in the route according to the following sequence:

Table 2. Number of cases (N_j) to consider in strategy $wLTI$ depending on the number of traffic lights (j).

j	1	2	3	4	n
N_j	3	9	23	53	$N_{n-1} + 2(1 + N_{n-1} - N_{n-2})$

In order to consider a large number of traffic lights within the route a more sophisticated optimization strategy than brute force, e.g. Dynamic Programming, should be applied.

(iii) Optimal speed profile to minimise fuel consumption with traffic light information (F^{opt}): This strategy considers the application of Dynamic Programming to the Optimal Control Problem of minimising fuel consumption while covering the distance L in a limited time T, provided that the vehicle cannot pass a Traffic Light in red.

(iv) Optimal speed profile to NO_x emissions with traffic light information (NO_x^{opt}): This strategy considers the application of Dynamic Programming to the Optimal Control Problem of minimising NO_x emissions while covering the distance$L$ in a limited time T, provided that the vehicle cannot pass a Traffic Light in red.

Table 3 summarises the main characteristics of the evaluated strategies:

Note that strategies (iii) and (iv) require a model for the estimation of fuel consumption and NO_x emissions.

Table 3. Description of the assessed strategies.

Strategy	Objective	Traffic Light Information	Real Time
$woTLI$	no	no	yes
$wTLI$	no	yes	yes
F^{opt}	fuel	yes	no
NO_x^{opt}	NO_x	yes	no

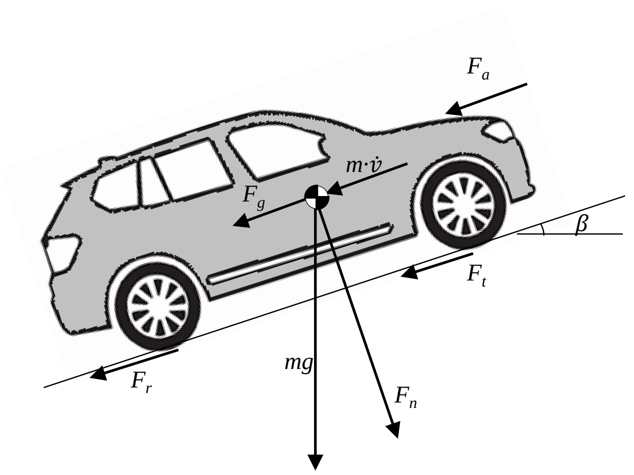

Figure 3. Scheme of longitudinal forces acting on a vehicle.

Details regarding the optimisation performed for those will be provided in following sections after describing the model used.

Vehicle model

In line with works of[13,14], the vehicle is modelled attending exclusively to longitudinal dynamics, implicitly assuming that transverse dynamics are negligible. However, in the present work a causal implementation, i.e. the model input is the engine throttle while the output is the vehicle acceleration, has been used. Figure 3 shows the set of forces acting on the vehicle.

Non-conservative forces related with friction are represented by aerodynamic drag (F_a) and rolling resistance (F_r). On the one hand, aerodynamic drag depends on the vehicle's frontal area A, the drag coefficient C_d, which is mainly function of the vehicle shape and surface roughness, the air density and the square of the vehicle speed (v):

$$F_a = \frac{1}{2} A C_d \rho v^2 \tag{3}$$

On the other hand, rolling resistance is represented by:

$$F_r = \mu m_v g cos\beta \tag{4}$$

where μ is a friction coefficient, dependent on the tyre-tarmac contact, and therefore difficult to evaluate accurately, but generally assumed to be in the range of 0.01 to 0.015 for light duty vehicles. Regarding the rest of parameters, m_v is an equivalent vehicle mass accounting for the vehicle mass (m) but also for the inertia of the powertrain rotating parts, g is the gravity constant and β represents the road grade, that also leads to a force against the vehicle advance when it climbs (F_g) which expression is:

$$F_g = m_v g sin\beta \tag{5}$$

Note that the energy required to overcome F_g when the vehicle is climbing can be theoretically recovered when going downhill to the initial position. Finally, traction force comes ultimately from engine torque or from brakes, then:

$$F_t = \begin{cases} \frac{\eta_t(u_{gb}) M_{eng}(n_{eng}, u_{pedal})}{r_w R_t(u_{gb})} & \text{if } u_{pedal} > 0 \\ u_{pedal} \hat{F}_b & \text{otherwise} \end{cases} \tag{6}$$

where M_{eng} is a non-linear function depending on the engine speed (n_{eng}) and pedal (u_{pedal}) representing engine torque, in the case at hand a map based on experimental data. This torque is transferred to the wheels by means of the transmission, which efficiency (η_t) and ratio (R_t) depend on the selected gear (u_{gb}). Particularly, in the current model, both η_t and R_t are affine functions of u_{gb}. The wheel radius necessary to pass from torque to force is represented by r_w. When breaking, the force applied to the wheels is proportional to a maximum breaking force ($\hat{F}_b$) through variable u_{pedal}. Note that for simplicity the following assumptions have been considered:

- The clutch is not modelled, so potential losses in this element during normal operation should be included in η_t while slipping during gear change is neglected.
- For the sake of model simplicity, both throttle and breaking pedals are modelled with a single variable (u_{pedal}) ranging from -1 to 1. This assumption involves that situations where both pedals are actuated at the same time cannot be modelled. Fortunately, this kind of driving is outside of the scope of fuel or emission minimisation strategies.
- A gear policy defines the gear to be applied depending on the vehicle speed. This policy has been chosen in order to limit the engine speed range to $(1250, 2500) rpm$.

Finally, a simple force balance leads to the following ordinary differential equation:

$$m_v \dot{v} = F_t - F_a - F_r - F_g \tag{7}$$

which is the main equation of the vehicle longitudinal dynamics. While the parameters in equations 3 to 6 can be obtained experimentally or estimated from literature, equation 7 allows tracking the velocity evolution as a function of an initial state, the driver actuation (u_{pedal}, u_{gb}) and problem perturbations such as the road grade.

Engine model

Within the elements of the vehicle powertrain, the engine is the more complex due to the large amount of energy transformations and physical processes involved. This complexity leads to almost impossible real time modelling capabilities for detailed engine physical models. In addition, the high number of states of high fidelity models make optimisation an impossible task since the computational burden of optimisation algorithms strongly depends on the number of states of the model. In this sense, a typical approach is to assume that engine dynamics are not relevant or at least their characteristic times are much lower than those of the pedal actuation. In this sense, in the vehicle model, the engine torque, the fuel consumption and NO_x emissions

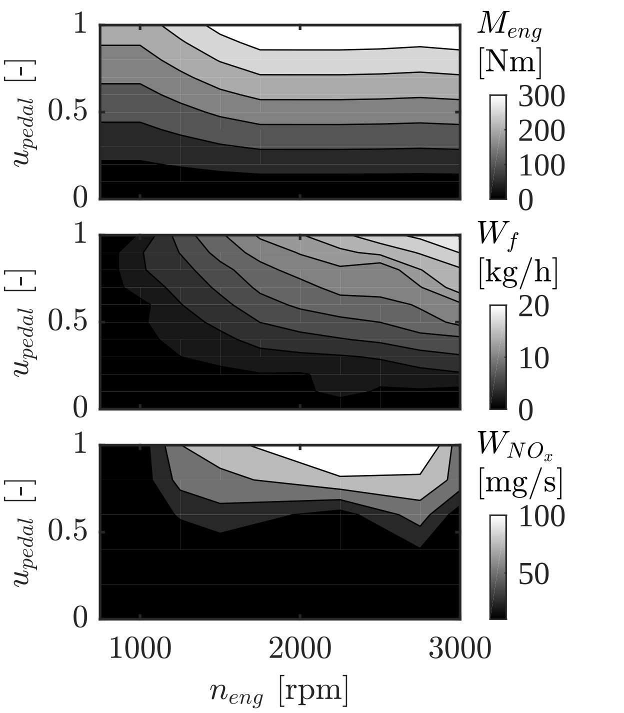

Figure 4. Experimental engine maps for torque (M_{eng} in upper plot), fuel consumption (W_f in medium plot) and NO_x emissions (NO_x in lower plot) used as quasi-steady engine model.

are calculated by simple interpolation of experimental data as a function of engine speed (n_{eng}) and load (u_{pedal}). The corresponding maps shown in figure 4 have been obtained experimentally in the chassis dynamometer.

Fuel consumption and NO_x optimisation

In the case of strategies (iii) and (iv), the model previously described has been used to calculate the vehicle speed sequence that minimises a given cost function (the fuel consumption or NO_x emissions respectively). In this sense, the associated Optimal Control Problem (OCP) can be expressed as:

$$\begin{aligned}
& min\left\{\int_0^L \frac{h}{v} dl\right\} \\
& s.t. \\
& \frac{dv}{dl} = \frac{f}{v} \\
& \frac{dt}{dl} = \frac{1}{v} \\
& v(0) = 0 \\
& v(L) = 0 \\
& t(0) = 0 \\
& t(l_{TL1}) = t_{green,TL1} \\
& t(l_{TL2}) = t_{green,TL2} \\
& t(L) \leq T
\end{aligned} \tag{8}$$

where the function h represents the fuel consumption (W_f) in the case of strategy (iii) or the NO_x emissions (W_{NO_x}) in case of strategy (iv). Function f represents equation 7 and $t_{green,TLj}$ represents the time range when the traffic light j is green. From the OCP presented in 8 one can observe that:

- While the typical domain for OCPs is time, in this case, space (l) has been selected since it presents a more natural domain to include constraints related to traffic lights whose position is constant. The same approach is usually followed when constraints on the road gradient or vehicle speed limits are to be considered [15]
- The problem defined in 8 has 2 states (v and t) and only one decision variable (u_{pedal}). In this sense, as the number of states and control variables is small, the problem is specially well suited for the application of Dynamic Programming (DP). In particular, the DP solver used in this work is a Matlab based code presented in [16].

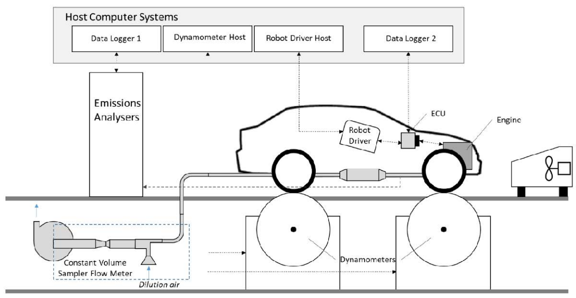

Figure 5. Chassis dynamometer layout illustrating key measurement and data acquisition devices.

Experimental set up

A 2014 diesel vehicle meeting EURO 5 emissions specifications was used in this work. The vehicle specifications are given in table 4. The vehicle was installed on a twin axle chassis dynamometer as shown in figure 5. Even though the vehicle in this study was 2-wheel drive, the rear wheels were motored to avoid vehicle controller errors during testing. The dynamometer is situated within a climatic chamber that controls temperature and humidity. The vehicle was driven by a Strahle Autopilot SAP2000 robot. Vehicle cooling was provided by an WLTC specification frontal fan where fan speed was controlled as a function of vehicle speed.

Table 4. Test vehicle specifications

	Vehicle
Engine displacement	2.0L
Max. power	100 kW
Max. Torque	320 Nm
Emissions level	EURO 5
After-treatment	DOC + DPF
Unladen mass	1800 kg
Gearbox Manual	6 Spd

Data logging was undertaken from four separate computer systems:

1. An Influx Technologies Rebel data logger was connected to the vehicle ECU through the On-board diagnostics (OBD) port and measured approximately 70 different data channels relating to the engine control system.
2. The robot host computer which logged all information relating to the robot pedal positions, pedal actuation forces and internal controllers.

3. An AVL RoadSim dynamometer host computer which logged speeds and forces on the individual axles of the system.
4. A Sierra CP Cadet test cell control computer which logged all information from emissions analysers.

In total around 150 data channels were recorded across all the data systems and all data was logged at 2 Hz (which was limited by the OBD logger).

In this work, the two key metrics from the experimental investigation are the fuel consumption and the NO_x emissions. For fuel consumption, it was decided to use the estimated fuel injection quantities from the engine controller. ECUs will usually contain signals giving an indication of the amount of fuel being injected into the cylinder. It is important to note that this is not a measurement, but rather a calibrated value within the ECU. Nevertheless, this fast signal can be a reasonable estimate of fuel consumption that offers a high resolution during transient events. In a modern engine, the numbers are usually available as a mass of fuel injected for each individual injection, and therefore the total fuel consumption is obtained by summation of the n individual injections as shown in equation 9. For the test vehicle in this work, up to 4 individual injections were observed during normal running.

$$\dot{m}_f = \frac{2N_{eng}}{60} \sum_{i=1}^{n} m_{f,i} \tag{9}$$

where N_{eng} is the engine rotational speed (rev/min) and $m_{f,i}$ is the fuel injected in grams during an engine cycle for injection number i of a total number of injections n.

NO_x emissions concentrations were sampled using a Horiba MEXA ONE system with the sampling point located downstream of the Diesel particulate filter (DPF) and Diesel oxidation catalyst (DOC). The mass flow of NO_x is them obtained using equation 10 where the exhaust mass flow ($\dot{m}_{exh}$) is calculated from the air mass flow and fuel mass flow obtained from the engine management system.

$$\dot{m}_{NO_x} = \dot{m}_{exh} c_{NO_x} u_{NO_x} \tag{10}$$

where c_{NO_x} is the NO_x concentration in the exhaust gas and u_{NO_x} is a constant value obtained from emissions measurement standards[17].

Results

Independently on the availability of information concerning the state of the traffic lights, the starting time of the route with respect to the traffic light period, is a variable that is outside of control, at least this is the hypothesis followed in this work. In addition, it is obvious that the performance of any given strategy will strongly depend on the traffic light timing, and therefore on the instant of the traffic light period in which the travel starts. According to that, in the present work the timing of the traffic lights when the trip starts has been considered as a stochastic variable uniformly distributed between 0 and T_{TL} (being T_{TL} the period of the traffic lights, in particular, 90 s according to table 1). Then, any arbitrary performance index h (in practise fuel consumption or NO_x emissions) of a given strategy will be evaluated in terms of the expected value considering the average of the results obtained with different starting times (dT) distributed along the complete traffic light period.

To point out the impact of the traffic light at the beginning of the trip on the vehicle trajectory, figure 6 shows the vehicle trajectories at 6 different timings (dT) of the 90 seconds period. In any of the trajectory plots (space as a function of time), the horizontal thick black lines represent the instants when traffic lights 1 and 2 remain red, the lines in grey scale represent the trajectories followed by vehicles with strategies $woTLI$ (in thick light grey line), $wTLI$ (black dotted line), F^{opt} (grey thick line) and NO_x^{opt} (in dark grey). It can be observed how the driver without Traffic Light information ($woTLI$) starts the trip with the same constant velocity independently on the starting time (dT). In particular, he follows a constant velocity profile (without considering the acceleration and breaking phases at the beginning and end of the trip) excepting cases $dT = 0$, $dT = 60$ and $dT = 75$ when the red state in any of the traffic lights forces the driver to stop. One may observe how in those cases, the driver needs to increase the velocity after the vehicle stop in the traffic light to make up for the time lost. In particular, in the case of $dT = 75$, despite increasing the vehicle velocity up to $50kmh$ (maximum allowed vehicle speed) after the stop in the second traffic light, the driver is not able to fulfil the time constraint and needs more then 150s to cover the travel length.

In spite of the fact that the fuel consumption in the cases without stop at the traffic lights may be low, cases $dT = 0$, $dT = 60$ and $dT = 75$ (and others around the same timing) where the vehicle needs to stop will harm the expected fuel consumption of the vehicle.

Strategy $wTLI$ coincides with $woTLI$ when no breaking due to traffic lights is required. In cases when the $woTLI$ strategy requires to stop the vehicle in a traffic light, the strategy $wTLI$ corrects the velocity profile to avoid hard breaking and subsequent acceleration.

Regarding the optimal strategies (F^{opt} and NO_x^{opt}) results show that a higher velocity at the first phases of the trip is preferable. The reason is that a faster acceleration and velocity during the first phases of the test allows the vehicle to coast at latter phases so there is not an associated fuel consumption nor NO_x emissions during those phases. Differences between F^{opt} and NO_x^{opt} trajectories are due to the fact that high efficiency areas in the engine do not correspond with low NO_x operating conditions. In fact, F^{opt} trajectories generally show more aggressive accelerations since the maximum efficiency area of the engine is placed at high loads, while the NO_x^{opt} strategy shows slower accelerations and velocities (see the slope of the trajectories plotted in 6) because the minimum NO_x emissions are obtained in the low engine speed and load area (see figure 4) where EGR is implemented. It can also be observed how in some cases (e.g. dT=60) NO_x^{opt} and specially F^{opt} trajectories lead to cover the distance in a time substantially lower than the limit. In those cases, the particularities of the engine maps make more efficient (in fuel or in NO_x) to spend more mechanical energy than strictly necessary to make the engine work in a convenient operating condition.

Figure 7 and 8 show the experimental results obtained for the case of $dT = 0$. In this particular case, if the $woTLI$

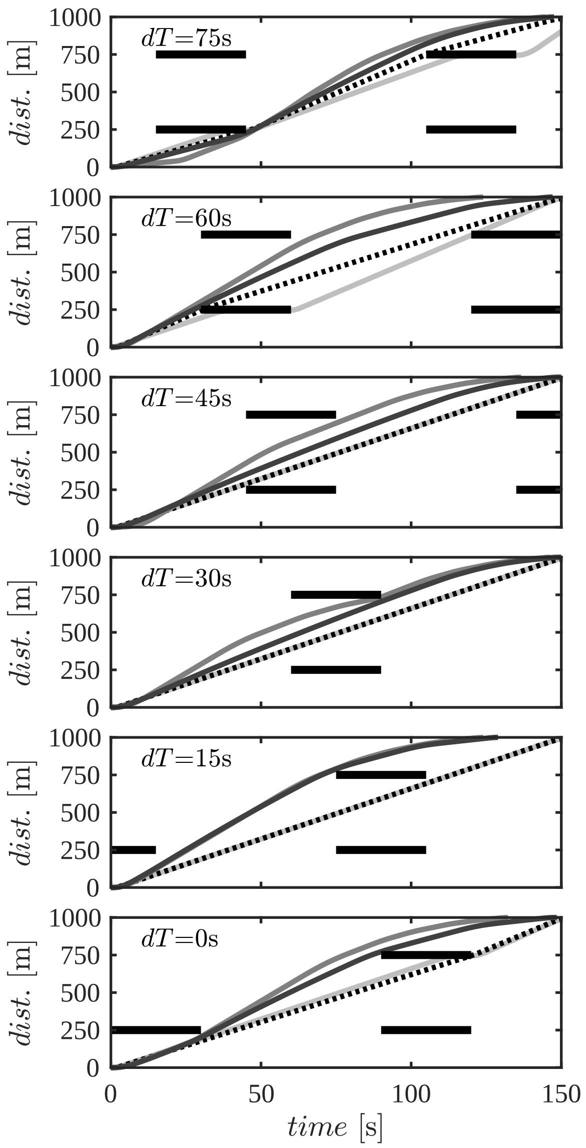

Figure 6. Vehicle trajectories at 6 different traffic light timings (dT). Light grey line: trajectory without traffic light information ($woTLI$). Black dotted line: trajectory with real time strategy and traffic light information ($wTLI$). Thick grey line: trajectory with Dynamic Programming optimisation for minimum fuel consumption (F^{opt}). Dark grey line: trajectory with Dynamic Programming optimisation for NO_x emissions (NO_x^{opt})

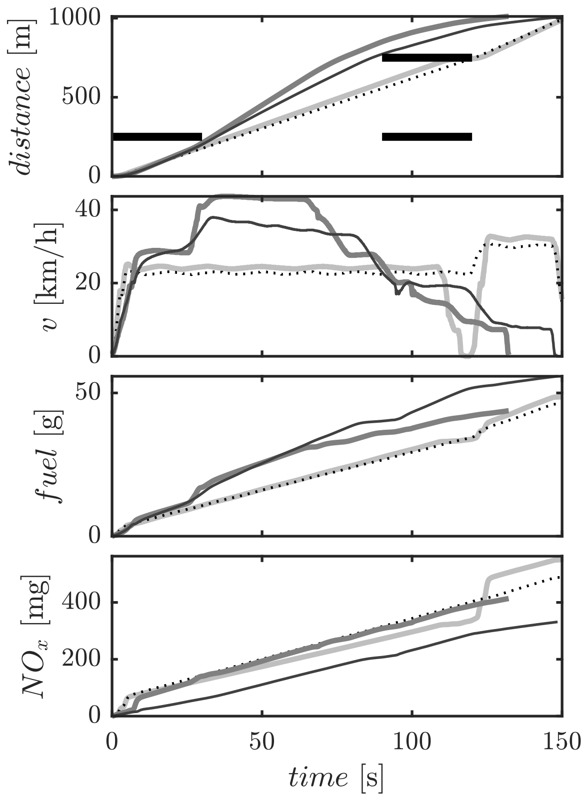

Figure 7. Experimental results (trajectories in upper plot, velocity profiles in second plot, fuel consumption in third plot and NO_x emissions in bottom plot) obtained for the case with dT =0s. Light grey line: trajectory without traffic light information ($woTLI$). Black dotted line: trajectory with real time strategy and traffic light information ($wTLI$). Thick grey line: trajectory with Dynamic Programming optimisation for minimum fuel consumption (F^{opt}). Dark grey line: trajectory with Dynamic Programming optimisation for NO_x emissions (NO_x^{opt}).

results are observed it can be noticed how the vehicle is not able to cover the complete distance (L) with a constant speed (L/T) since it finds the second traffic light in red and needs to stop. Then, in after the second traffic light the vehicle needs to accelerate to a higher velocity to make up for the time lost. Note that this acceleration is the responsible of a considerable percentage of the NO_x emitted and also leads to a substantial increase in the fuel consumption. The results with the $wTLI$ strategy show a slower vehicle speed until the second traffic light that allows the vehicle to reach this point just when the traffic light turns into green. Of course, some acceleration is needed after this point to recover the time lost due to a lower vehicle speed than necessary to cover the distance in time T =150s but this acceleration is smaller than in previous case, no substantial NO_x or fuel increase is observed. Both optimal strategies (F^{opt} and NO_x^{opt}) involve a high acceleration at the beginning up to a velocity level that allows to pass the first traffic light just after getting green. It can be noticed how the acceleration in the NO_x^{opt} case is slightly lower to avoid high loads where NO_x production is high. After this point, the velocity is again increased up to the maximum velocity in the cycle to allow the vehicle pass through the second traffic light before getting red, and then the vehicle speed is slowly reduced to the end of the route. Note that in both cases the vehicle needs less than 150s to cover the distance as this condition has been included as a constraint for the optimisation problem. In particular, the F^{opt} case requires only 132s since the maximum efficiency area of the engine is placed at a higher load than that required to cover the distance in 150s.

Similarly, figures 9 and 10 show the experimental results obtained for the case of $dT = 45$. In this particular situation, $woTLI$ and $wTLI$ solutions are exactly the same since keeping a constant velocity during the complete route of L/T does not involve crossing any traffic light in red. Optimal trajectories (F^{opt} and NO_x^{opt}) are again based in a maximum acceleration then cruising or coasting and finally breaking pattern. In any case, it can be observed how, as in this case the impact of the traffic lights on the $woTLI$ and $wTLI$ strategies is minimum, the differences in performance

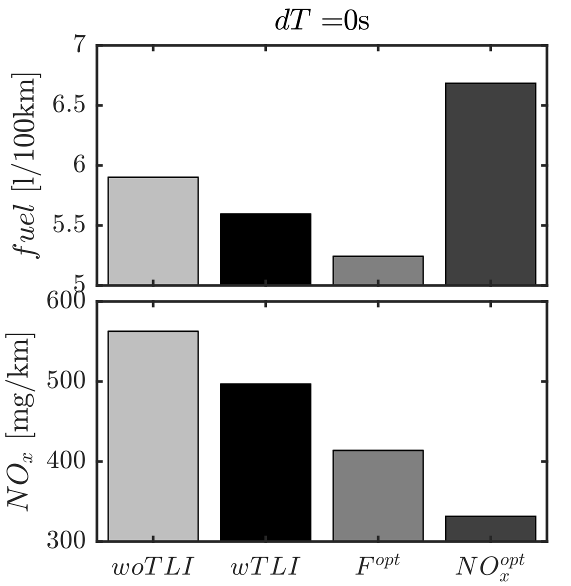

Figure 8. Accumulated fuel consumption (top plot) and $\mathrm{NO_x}$ emissions (bottom plot) obtained for the case with dT =0s.

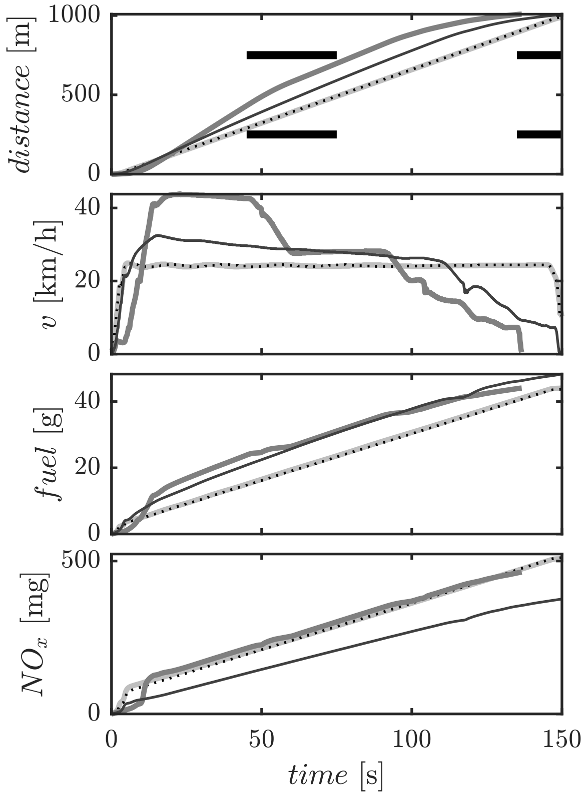

Figure 9. Experimental results (trajectories in upper plot, velocity profiles in second plot, fuel consumption in third plot and $\mathrm{NO_x}$ emissions in bottom plot) obtained for the case with dT =45s.Light grey line: trajectory without traffic light information ($woTLI$). Black dotted line: trajectory with real time strategy and traffic light information ($wTLI$). Thick grey line: trajectory with Dynamic Programming optimisation for minimum fuel consumption (F^{opt}). Dark grey line: trajectory with Dynamic Programming optimisation for $\mathrm{NO_x}$ emissions (NO_x^{opt}).

between those strategies and the optimal ones (particularly in terms of fuel consumption) is reduced.

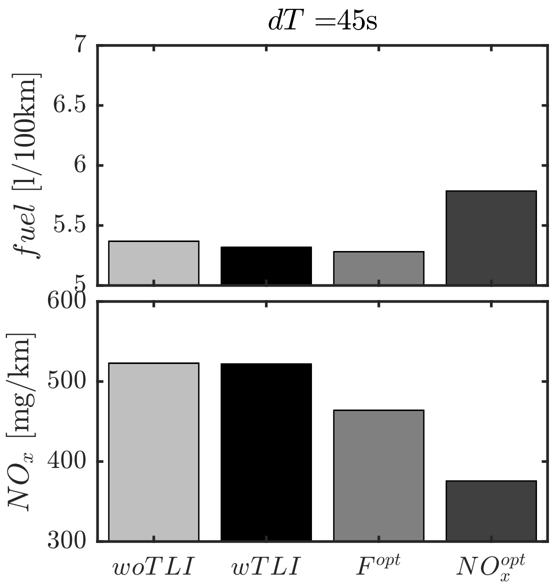

Figure 10. Accumulated fuel consumption (top plot) and $\mathrm{NO_x}$ emissions (bottom plot) obtained for the case with dT =45s.

Figure 11 shows the average results obtained for the 6 different dT timings shown in 6 as an estimation of the expected performance of the vehicle in the considered route. In average, a driver trying to keep a constant speed without traffic light information ($woTLI$) will have a fuel consumption of $5.9l/100km$ and produce $612g/km$ of $\mathrm{NO_x}$ emissions. Including information about the state of the traffic lights allows to reduce the fuel consumption to $5.45l/100km$ (-7.6%) and $\mathrm{NO_x}$ emissions to $533g/km$ (-12.9%) despite not using any vehicle model nor fuel consumption or $\mathrm{NO_x}$ optimisation that may require high computation efforts. As expected including computation capabilities aimed to model the actual vehicle performance and allowing its optimisation leads to an additional improvement in the considered performance index. In this sense, a fuel oriented optimisation will lead to a fuel consumption of $5.18l/100km$ (-12.2%) and $\mathrm{NO_x}$ emissions of $449g/km$ (-26.6%). If the objective is to minimise the $\mathrm{NO_x}$ emissions, they can be reduced up to $415g/km$ (-32.2%) at the expense of increasing fuel consumption to $6.4l/100km$ ($+8.5\%$).

Conclusions

This paper has aimed to assess the impact of traffic light information availability in terms of fuel consumption and $\mathrm{NO_x}$ emissions. In order to do that, a non-linear dynamic vehicle model has been developed to evaluate the performance of a vehicle in terms of fuel consumption and $\mathrm{NO_x}$ emissions in a route with different scenarios of information about the state of the traffic lights. In particular, three cases have been studied: the case without information about the state of the traffic lights, a case where the state of the traffic lights is known but suboptimal strategies have to be used due to computation capabilities limitations and finally the case where the state of the traffic lights is known and there are not computation limitations, so optimal control (DP) can be used. Previous strategies have been used with fuel consumption and with $\mathrm{NO_x}$ as optimisation objectives

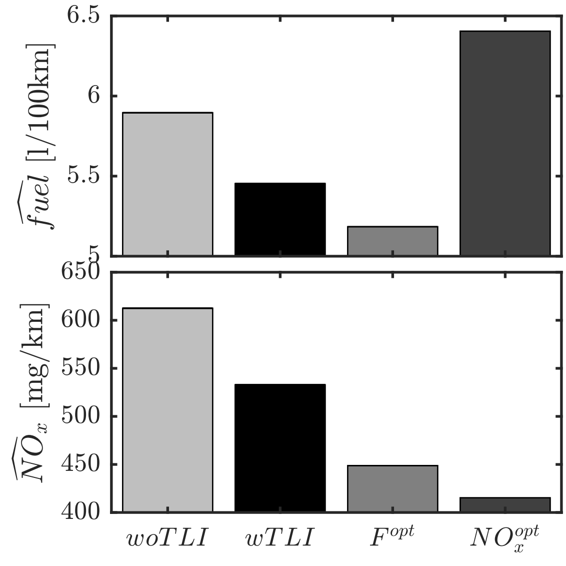

Figure 11. Average fuel consumption ($\widehat{fuel}$ in top plot) and NO_x emissions ($\widehat{NO}_x$ in bottom plot) for the six traffic light timings dT tested (see figure 6.

to check the impact of the solution on both parameters. The obtained trajectories have been evaluated experimentally in a chassis dynamometer with a Euro5 Diesel light duty vehicle.

From the authors' point of view, the important contributions of this work are the following:

- An efficient management of vehicle speed is a key factor for fuel minimisation, providing reductions within 7 and 12% depending on the complexity-optimality of the strategy used, even when the reference case ($woLTI$) was a strategy aimed to keep constant velocity, which is not the worse scenario for fuel consumption. One may note that this level of reduction is, by far, higher to what can be attained with optimisation of the engine control itself. Accordingly, driver education and driver assistance systems are key for fuel consumption reduction.
- An efficient management of vehicle speed is even more important for NO_x emissions reduction since they may provide reductions within 13 and 32% depending on the complexity-optimality of the strategy used.
- Traffic light information is essential for vehicle speed management, even if suboptimal strategies are used, substantial reductions in terms of both fuel consumption (7%) and emissions (12%) may be obtained.
- The engine trade-off between fuel consumption and NO_x, and the differences in the engine operating conditions for high efficiency and low NO_x emissions lead to substantially different vehicle speed profiles depending on the optimisation objective, and in particular a noticeable penalty in fuel consumption if NO_x emission minimisation is pursued.

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